Does money matter? A theory-driven growth mixture model to explain travel-mode choice with experimental data

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Abstract: In the present article we apply a growth mixture model using Mplus via STREAMS to delineate the mechanism underlying travel-mode choice. Three waves of an experimental field study conducted in Frankfurt Main, Germany, are applied for the statistical analysis. Five major questions are addressed: (1) whether the choice of public transport rather than the car changes over time; (2) whether a soft policy intervention to change travel mode choice has any effect on the travel-mode chosen; (3) whether one can identify different groups of people regarding the importance allocated to monetary and time considerations for the decision of which travel mode to use; (4) whether the different subgroups of people have different initial states and rates of change in their travel-model choices; (5) whether sociodemographic variables have an additional effect on the latent class variables and on the changes in travel-mode choice over time. We also found that choice of public transportation in our study is stable over time. Moreover, the intervention has an effect only on one of the classes. We identify four classes of individuals. One class allocates a low importance to both monetary and time considerations, the second allocates high importance to money and low importance to time, the third allocates high importance to both, and the fourth allocates a low importance to money and a high importance to time. We found no difference in the patterns of travel-mode changes over time in the four classes. We also found some additional effects of sociodemographic characteristics on the latent class variables and on behavior in the different classes. The model specification and the empirical findings are discussed in light of the theory of the allocation of time of Gary Becker.

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Key words: latent class analysis; growth mixture modeling; travel mode choice; STREAMS; M*plus*; intervention study.

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Introduction

Empirical studies in general and applications of structural equation modeling in particular often fail to recognize population heterogeneity. Data are analyzed as if they were collected from a homogenous population. However, if it is not taken into account, parameter estimates might be biased.

There are several examples where populations might be heterogenous. In education studies, different classes might have a different background. In studies of attitudes and opinions the homogeneity assumption of standard measurement models may not be realistic across subsets of groups. For example, the validity and reliability of items is expected to differ across subgroups defined by religion, age, gender, place of residence, income, social economic status and so on (Muthén, 1989). An alternative view to the homogeneity of a sample is to treat the data as coming from heterogenous populations, each having its own set of parameter values.

The theory of finite mixture modeling assumes that the population of interest is not homogenous, but consists of heterogenuous subpopulations with varying parameters. Mixture models are discussed in the context of latent class models (e.g. Hagenaars & McCutcheon, 2002). The common theme of mixture modeling is to partition the population into latent classes or subpopulations with class membership determined by specific parameters (Li, Duncan, Duncan & Hops, 2001).

Growth modeling has become a standard tool in the examination of change over time and the impact of interventions across time. One common way to estimate a growth model is by using latent growth modeling (e.g. Bollen & Curran, 2006). This literature uses random effects to represent an individual's linear or non-linear change curve, and covariates such as socio-demographic background variables to account for variations in these curves.

Recently, Muthén (2001a,b) proposed an extension of the latent growth model methodology, which incorporates mixture models in the so called growth mixture models. These models combine categorical and continuous latent variables into one model. Muthén and Shedden (1999) generalized it to the general growth mixture modeling framework (GGMM). The GGMM approach allows for unobserved heterogeneity in the sample, where different individuals can belong to different subpopulations. In such a way multiple developmental trajectories can be estimated, each within a population. The model can be further extended to estimate varying class membership probability as a function of a set of covariates and to include outcomes of the latent class variable (Li et al., 2001). An individual has a certain trajectory class membership that does not change over time (for details on the specification of a growth mixture model see for example Muthén & Shedden, 1999, Muthén, 2001a,b or Muthén & Muthén, 2000, 2001).

The following paper presents an application of growth mixture modeling to an intervention study on travel mode choice. It contributes to the literature in four main aspects: (1) using real data rather than simulated data to test a growth mixture model; (2) collecting the data in an intervention field study with experimental and control groups; (3) conducting a theory-driven test and thus combining substantive theory with newly developed methods to test behavior over time; (4) identifying different classes of people regarding the importance they allocate to time and money considerations for the future development of policies to reduce car use. Applications of GGMM models with real data from an experimental field study have been done seldom. In our study individuals are randomized into a control group and an intervention group, and their travel mode choice is measured repeatedly three times. The strength of randomized repeated measure studies is that they allow assessing the effect of the intervention not only at one time point directly after the intervention, but also on the whole trajectory. Development at either the experimental or the control group needs to be described in terms of unobserved trajectory classes of development, within which there may be further individual trajectory variation (Muthén et al., 2002). However, Kühnel (1999) has argued that the exploratory use of latent class analysis to conduct mixture modeling may easily lead to artifacts in the findings. Therefore, we apply the mixture modeling approach in a theory driven way.

In the next sections we will give a short description of the theoretical background, describe the method, then the intervention field study and the sample. Afterwards we will present the data, the variables and the results. We will finalize with a discussion of the results in light of the theory of the allocation of time of Gary Becker.

Theoretical Background

Micro- and macroeconomic theories deal intensively with the influence of the attribute "price" on the economic behavior. Price is the value that a vendor receives in return to his product from the buyer, since the price of this product presumably represents its quality. During the purchase, the buyer must use financial means from his income in the size of the price of the product. People can buy products whose prices cannot exceed their total income. Hence, the influence of the attribute "price" on the economic behavior rests on the income restriction (Davidov, Schmidt & Bamberg, 2003). In the context of travel mode choice, private car users could be persuaded from the economic perspective to use more ecological public means of transportation by using the "price" instrument. Measures such as gasoline taxation or road taxation are expected to increase the price and therefore to reduce the use of the private cars.

However, it has been found that price is not the only restriction influencing behavior. Becker (1965) proposed that "time" becomes a clear factor and resource in addition to money when households are considered. In such a way time has a value, which can be expressed by money, and individuals belonging to households take into account both monetary and non-monetary time restrictions when they maximize their utility. That is, not only price but also the time cost will determine behavior. In the context of travel mode choice, a longer duration of travel with the mean of transportation chosen is considered by individuals as an increase in its total price. In Davidov, Schmidt and Bamberg (2003) it is demonstrated that both monetary and time restrictions have a significant effect on behavior in the empirical context of travel mode choice using a representative sample of the German population. Higher time and monetary costs affect negatively the use of the respective travel mode.

This result can be applied in the design of intervention studies to change travel mode to a more ecological one. Intervention studies can reduce for example monetary and non-monetary costs of public transportation in order to test the increase of their use. However, Becker does not postulate in his theory whether the effect of the monetary and time restrictions may differ across individuals, that is he implicitly assumes homogeneity of samples. It is also not clear from his study whether all individuals weigh monetary and time considerations equally in their choice of travel mode, or whether they consist of subpopulations, which seize both restrictions differently. In Becker's theory this remained an open question. However, it may be the case that for some people monetary restrictions determine behavior more strongly than for others. Similarly, for other people time considerations may be more important, and for another group of people both money and time may be important. Identifying such groups has implications for future development of policies to reduce car use.

Additionally, Becker postulates in his theory that socio-demographic characteristics will be reflected by the monetary and time costs. However, empirical findings suggest that they may have a direct and unique effect on behavior in addition to the effect of monetary and time considerations. In Davidov et al. (2003) it was demonstrated that some socio-demographic characteristics such as gender, marital status and age as well as monetary considerations (affected by income) have an effect on behavior[1]. Furthermore, in Davidov (submitted) an empirical support was given for the positive effect of education and availability of a car on car use. We also believe that number of children should have an effect on travel mode choice because of the higher need of flexibility, which can be achieved by using the car. In the following sections we test: 1) a growth mixture model to identify subpopulations or classes of money and time; 2) in addition we estimate the effect of the socio-demographic variables on behavior and on the latent classes using data from an experimental field study to change travel mode choice in Frankfurt (Germany).

The current study is theory-driven in the sense that theory helps to postulate what variables play a role in the explanation of behavior (for a critique on inductive model testing in the context of mixture modeling see Kühnel, 1999). However, theory does not help us to predict what would be the change in behavior, nor the number of classes. Indeed, Muthén (2002) discusses a general model, which integrates continuous and categorical latent variables. Nevertheless, we find that theoretical propositions are often formulated for the special case of continuous latent variables but not for categorical ones including latent class and latent growth variables. As statistical tools develop, and methods evolve to estimate unobserved heterogeneity and change over time, theories have to be reformulated to adapt to developments in possibilities of empirical testing.

We will ask the following five questions:

1) whether the choice of public transport rather than the car changes over time;

2) whether a soft policy intervention (according to Action Theory; see for example Bamberg & Schmidt, 2001) to change travel-mode choice has any effect on it according to the wide version of rational choice (Opp, 1999);

3) whether one can identify different classes of people regarding the importance allocated to monetary and time considerations for the decision which travel-mode to use;

4) whether the latent class variable has an effect on the growth model;

5) and whether socio-demographic variables have an additional effect on the latent classes and on the changes in travel-mode choice over time. This would be in line with the wide version of rational choice (for a discussion see Opp, 1999).

Method

Muthén and Muthén (2001) extend the SEM framework to allow estimation of several classical types of models such as latent class analysis. The combination of categorical latent variables together with the general latent variable framework also allows to specify new types of models. Examples of such models are structural equation models with mixtures, models that combine latent class analysis with structural equation modeling, mixture discrete-time survival analysis or growth mixture modeling (Muthén & Muthén, 2003; see also Gustafsson & Stahl, 2001, 2004a, 2004b). The categorical latent variables may be measured by categorical variables (latent class indicators) or by continuous variables. The categorical latent variables may also be regressed onto observed background variables.

In this paper we are considering a mixture growth model, which combines a latent growth model with mixture modeling. The mixture part of the model includes a latent class variable defined by the number of classes and measured by several manifest variables. The latent growth part of the model includes a slope and an intercept latent variable, which measure the developmental trajectory over time (for details on growth modeling see for example Curran & Muthén, 1999 and Bollen & Curran, 2006). The latent slope and the latent intercept are dependent on several background variables. The regression slopes are allowed to be different for the different classes.

We are going to present the growth mixture model, specify and test it under the STREAMS environment. The advantage of STREAMS is that it handles the modeling process in a step-by-step manner. The simple structured model is estimated first and its estimates can be used as starting values for the more complex models. In this way STREAMS overcomes the "well-known" starting value and convergence problems in most other SEM programs (for more details on the program STREAMS see Gustafsson and Stahl, 2000, 2004b).

In order to create a mixture model in STREAMS one has to state for the categorical latent class variable the number of classes. Each class is technically referred to in two ways: with the freely chosen class label (e.g., Cl 1) and with the assigned category label (e.g., C#1). This double notation is required by the programming language, since it allows reference to both population membership (e.g., Cl 1) and latent categorical variables (e.g., C#1). In appendix A we report the syntax commands under the STREAMS environment with a short explanation (for more details see Gustafsson & Stahl, 2001: 51-75).

Sample

The data were collected in three waves of an intervention study, which should evaluate travel mode choice in Frankfurt Main (Germany) and the effect of a soft-policy intervention on behavior. 5,000 randomly selected inhabitants of the city of Frankfurt, who are also car drivers, received a questionnaire by mail at the end of September 2001. A reminder was mailed in October 2001. In November 2001 there was an additional reminder. 1,337 of the questionnaires were sent back by the end of January 2002, which resulted in a response rate of 26.7%[2]. In May 2002, the second questionnaire was sent by mail to the 1,337 respondents of the first wave. About 75% of them were exposed to the intervention. They received together with the second questionnaire information on available public transportation in Frankfurt. 977 people responded to the second questionnaire within 6 months (a response rate of 73%). The third questionnaire was sent in November 2002. 792 of the participants of the second wave returned and completed the questionnaire (a response rate of 81%). The time gap between the waves was similar, and questionnaires always reached respondents within a 5-day period. The analysis is based on responses of 774 inhabitants, who had reported at least one trip in each wave on the selected day using the car or public transport. The intervention was aimed to change travel mode choice in the short run as well as in the long run. This will be tested in our empirical example.

Variables

Travel mode choice: was derived from a protocol filled in by the subjects about all the travels conducted on that day and the means of transportation used. From this protocol the behavioral variable was created. It received the value of 1 if a subject did not use the car (but walked, rode a bicycle or used public transport) on his second reported way on that day, and zero otherwise. The behavioral variable of the second reported day is of interest, because the first reported way was often to work and not to other destinations[3]. We collected data on this variable in three waves: before the intervention (BEH1B), during the intervention (BEH2B), and some months after the intervention (BEH3B).

INV1: is a dummy variable, which receives the value of 1 in case the subject belongs to the experimental group (and receives information on available public transportation in the town), and zero otherwise.

B104A , B104B and B104C_describe how much people care about monetary costs of using the car after the last increase of fuel prices. B104A is a variable describing anger on the expensive costs of using the car for daily use associated with the price increase of fuel. B104B measures whether one pays more than he is willing to pay for the daily car use. B104C measures the belief that using the car daily is too expensive. The response range was a five-step bipolar scale from 5 (totally agree) to 1 (totally disagree). B112B, B112C, B112D and B112F measure how much people care about time costs, if they decide to use in the next weeks in Frankfurt public transportation rather than the car. B112B measures the belief that using public transportation in the next weeks in Frankfurt rather than the car involves waiting a long time for the next connection. B112C measures the belief that using public transport rather than the car in Frankfurt will save the time costs and anger caused by looking for a parking place. B112D measures the belief that one will avoid traffic jams when using public transport rather than the car in Frankfurt. B112F measures the belief that using public transport in Frankfurt brings one to the destination more quickly than the car. The response range of the four items was a five-step bipolar scale from 5 (very likely) to 1 (very unlikely).

GEN1 receives the value of one for males and two for females and CHL1 is the number of children in the household. EDU1 is a continuous variable, which has the value of 1 for respondents who have not finished any school, 2 for respondents who obtained elementary school education, 3 for respondents who finished high school, 4 for respondents who finished high school and matriculated, and 5 for respondents with education higher than high school. INC1 is the net income of the household. It is measured in 7 categories ranging from 1 (less than 1000 Euros) to 7 (6000 Euros and more). AC1 is the availability of a car in the household. It ranges from 1 (always) to 4 (never).

Descriptive Overview

As shown in Table 1, 51%% of the respondents used public transportation, the bicycle or walked on the first wave, 50% on the second wave and 49% on the third wave. There seems to be no change in behavior on average, but it is not clear yet whether subgroups increased or decreased their car use in this time period. 75% were exposed to the intervention program. 52% were women, the average number of children in the household was 0.39, and the average level of education was between high school and high school with matriculation. The average net household income was between categories 2 (1000-1999 Euros) and 3 (2000 and 2999 Euros) (2.99 on average) and the average age 44. A car was available between always and sometimes on average in the household. According to the respondents' answers, they moderately care for the monetary costs associated with the last increase of fuel prices of using the car daily in Frankfurt (with mean values of 3.08, 2.89 and 3.07 for B104A, B104B and B104C respectively). They believe that if they use daily public transport rather than the car in the next weeks in Frankfurt, it is quite likely they will wait for a long time for the next connection (the mean of B112B is 3.74), it is quite likely they will save the time costs and anger caused by looking for a parking place or wait in the traffic jam (the mean of B112C is 4.00 and of B112D is 3.85). Finally, they believe that public transport will bring them to their destination in Frankfurt more quickly than the car (the mean of B112F is 3.86).

Table 1 About Here

In the analysis we will try to identify subpopulations, which consider these restrictions differently. We will test whether the changing process of travel mode choice varies for the different classes. The effects of socio-demographic characteristics and of the intervention will be compared across the different classes.

Estimating the Growth Mixture Model

Now we report the results of the growth mixture model to explain the change of travel mode choice and the effect of the intervention in Frankfurt. We use the M*plus* version 3.0 program via STREAMS. One advantage of M*plus* is that missing data (which increased with each wave in our data, especially for the behavior variable) is allowed in the estimation procedure. M*plus* uses the available information to estimate a model (with the EM algorithm and the MLR estimator) based on the covariance matrix of each pattern of missing data (for technical details and advantages of this procedure see Muthén, Kaplan & Hollis, 1987 and Muthén & Muthén, 2004).

In Figure 1 the model is graphically presented. On the left side the growth model of the three measurements of public transport use in Frankfurt (BEH1MB, BEH2MB and BEH3MB) is shown. The intervention variable (INV1) (receiving information) has a causal effect on behavior in the second time point. The slope and intercept latent variables are supposed to depict the growth trajectory (if any) of behavior over the three time points. The coefficients between the slope and the three time points are restricted to represent linear growth (see Bollen & Curran, 2006). The growth curve model and the latent class model were linked together by regressing the latent class variable on the growth factors. The demographic background variables GEN1, CHL1, EDU1, ALT1, INC1 and AC1 affected both the growth factors slope and intercept and the latent class variable, as depicted in the path diagram in Figure 1.

Figure 1 About Here

The latent class variable (according to our statistical analyses we find 3 categories, see Table 2) are measured by seven manifest variables (not shown in the figure). Three of them measure the monetary costs associated with using the car daily in Frankfurt since the increase of fuel prices (B104A, B104B, B104C). The other four manifest variables measure the time costs associated with using public transport rather than the car for daily use in Frankfurt in the next weeks (B112B, B112C, B112D and B112F). By using these variables we can find out whether people in our group of respondents can be associated to different classes of people regarding the importance allocated to monetary and time considerations for the decision which travel-mode to use. In the theory of Becker different classes are not specified. Therefore, we use as a baseline model the one-class model, and compare it empirically with models with more classes.

It is useful to describe the modeling process in relation to the results. STREAMS estimates models in a way that it breaks down the complex model into simple small models, and then links the models together by connecting the latent variables in each simple model according to the supposed relationship in the theory. So, we estimated the growth model, then the growth model with the intervention, the latent class model separately and then joined them into a growth mixture model. The process of estimating a latent class mixture model can be found in Gustafsson and Stahl (2001). We ran a non-mixture single population model to estimate the threshold/mean of the manifest variables. Then we estimated a latent growth curve model with 2 subgroups. A categorical latent variable was specified to identify the class belonging. Then we estimated a three subgroup model (Gustafsson & Stahl, 2001: 62). We continued to estimate the model with four and five classes. We compared the AIC, sample-size adjusted BIC, BIC and entropy in the different models (for details why we use the combination of these fit measures to decide on the number of classes see Dayton, 2003 and Muthén, 2001b). As one can see in Table 2, the four-classes model was the acceptable one with the highest entropy and a BIC, sample-size adjusted BIC and AIC lower than in models with a smaller number of classes[4]. It should also be noted, that when choosing the number of classes, one should rely not only on global fit measures, but on other arguments such as plausibility and contribution of additional classes. Therefore, whereas the BIC and AIC of a five-class model is even lower, an additional fifth class is relatively small, and is substantively not as meaningful as the other four classes. Thus, we ended up with a four-population model. 8% belonged to the first class, 17% belonged to the second, 44% belonged to the third class and 31% to the fourth.

Table 2 About Here

Figure 2 about here

We found mean structure differences in the four subgroups regarding the importance allocated to money and time. Figure 2 presents the four different profiles of subjects by showing the means of the monetary and time considerations in each class. There is no significant difference in the mean of B104A, B104B, B104C (monetary considerations) and B112B (time consideration) in classes 2 and 3, and also in classes 1 and 4. However, the means in classes 2 and 3 are significantly higher than in classes 1 and 4. We also find no significant difference in the means of B112C, B112D and B112F (time considerations) in classes 3 and 4, and in classes 1 and 2. However, the means in classes 3 and 4 are significantly higher than in classes 1 and 2. Thus (with the exception of B112B), we can conclude that class 1 generally allocates low importance to monetary considerations of using the car and to time considerations (saving time by using public transportation in Frankfurt); class 2 allocates a high importance to monetary considerations and a low importance to time considerations; class 3 allocates a higher importance to both monetary and time considerations; and class 4 allocates a lower importance to monetary considerations and a higher importance to time considerations.

There is no significant difference in the importance allocated to the waiting time for connections in Frankfurt between the classes (depicted in B112B).

All coefficients between the slope and the intercept to behavior are significant, and do not differ significantly in the four different classes. Table 3 presents the means of the slope and the intercept of the growth model in the four classes. Despite some differences in size, none of them turned out to be significantly different from zero ($p<0.05$). Thus, there seems to be no change in behavior across time. The intervention has a significant and positive effect on behavior only in the second class, which allocates a higher importance to monetary considerations (with a standardized coefficient of 0.11, not shown in the table). People in this class may be irritated by the rising costs of using the car, and may look for alternatives. This could explain the positive effect. However, as the slope of the growth model is zero in the second class, we can conclude that the intervention had no effect in the long run. Also the covariance between the slope and the intercept turned out to be not significant in the four classes. Thus, there was no relation between initial level and the changing process of behavior in any of the classes.

Table 3 about here

Table 4 about here

Table 4 presents differences in the effects of background variables on the intercept and the slope in the different classes. Availability of a car has a positive and significant effect on the intercept of behavior in the four classes. That is, regardless of the class to which one belongs, the lower the availability of a car, the higher the initial use of public transportation. Availability of a car has a significant effect ($p<0.1$) on the slope only in the first class, which allocates low importance to both money and time. In this class, the lower the availability of a car, the higher the slope of change towards public transportation use. There was no effect of availability of a car on the slope in other classes. Gender has a positive effect on the intercept in classes 2 ($p<0.1$) and 3 ($p<0.05$). That is, in the classes where individuals allocate high importance to monetary considerations and a low importance to time considerations (class 2) or a higher importance to both monetary and time considerations (class 3) women have a higher initial use of public transportation than men. In class 3, where time is considered important, women have a higher initial use of public transport than men. Age has an effect on the intercept only in class 4, where time is considered important. In this class, older people have a higher initial use of public transport than younger ones. Number of children have a negative effect ($p<0.05$) on the initial use of public transport in classes 3 and 4 (where time is important). In both classes, the higher the number of children, the lower the initial use of public transportation. It can be explained by a higher need for flexibility for these people, when children have to be driven to the kindergarten or to school for example. Number of children has a positive effect on the slope only in the third class. In this class money is also important, and the higher the number of children (which increases the household's costs) the higher the increase in the use of public transport. Education has a negative effect on the intercept in classes 1 and 2, and a positive effect in class 4. In classes 1 and 2 time is less important than in the other classes. In class 4 time is important. Classes 1 and 2 might be the status seeking group, for which saving time by using public transport is less important. They would use the car as a status symbol. The 4th class might be the more environmental one. In this group, people with higher education would tend to use public transportation. Finally, income has a positive effect on the intercept in the first class and a negative one in the fourth class. In the 1st class, where both money and time are considered less important than in other classes higher income has a positive effect on the initial use of public transport, similarly to the effect of availability of a car in this class. In the fourth class, where time is important, income has an opposite effect (but not as strong in absolute terms as the effect of education in this class on the intercept). Time may mean money for this class, and therefore would negatively affect the initial use of public transport. However, it has a positive effect on the change towards public transportation in the second class.

Finally, Table 5 provides a summary of the effects of the background variables gender, number of children and income on the latent class variable (see Figure 1, other background variables were omitted from the analysis because of multi-collinearity and convergence problems). As Table 5 shows, income has a positive ($p<0.1$) effect on the first latent class variable, and a negative ($p<.05$) effect on the third latent class variable. Having a higher income makes it more likely to belong to the first class, and less likely to belong to the third class. The first class attributes a low importance to money and time considerations. People in this class may be less irritated or affected by the increase in fuel prices, or by increasing costs of car use. They also believe less than other people that they would save time by using public transport. The third class attributes high importance to the two aspects of money and time. Thus, having a higher income is related to being categorized to the first or the third classes.

Table 5 about here

Discussion

This paper has discussed and applied growth mixture modelling to identify different classes regarding the importance allocated to monetary and time considerations in the decision which travel mode to use. Becker (1965) postulated that both restrictions should have an effect on behavior, but he did not implicitly postulate whether these effects should vary across individuals or subpopulations. We tried to test whether these considerations may be different across individuals. We have also asked for each class separately, whether the choice of public transport rather than the car changes over time; whether a soft policy intervention to change travel-mode choice has any effect on the choice; and whether socio-demographic variables have an additional effect on the classes and on changes in travel-mode choice over time. The methodology of growth mixture modelling allows one to examine in detail the impact of intervention and socio-demographic variables on unobserved subgroups characterized by different attitudes to time and monetary considerations. In addition, the analysis can predict the influence of subgroup membership on the outcomes.

We found that choice of public transportation in our study is stable over time in all classes. Nevertheless, we identify four classes of individuals. One class allocates low importance to both monetary and time considerations; class 2 allocates a higher significance to monetary considerations; the third class allocates a higher importance to both monetary and time considerations; and class 4 allocates a higher importance to time. We found no difference in the patterns of travel-mode changes over time in the four latent classes. However, the intervention had a positive effect on behavior in class 2. In

Becker's theory, provision of information is not expected to affect behavior, since individuals are assumed to posses all the information they need. The intervention seems to have generally no effect.

We found some significant and differing effects across classes of socio-demographic characteristics on the change in behavior as well as on the latent class. The strongest effect was that of the availability of a car: in all classes results showed a negative effect on the initial use of public transport, and a negative effect on change in the first class. Several other effects of socio-demographic characteristics on the intercept and the slope were in line with the literature (for example Bamberg, Davidov & Schmidt, in press), such as the effects of gender, education and number of children but in a few classes effects had the opposite direction. For example, in contrast to previous findings, in the fourth class education had a positive effect on the initial public transport use (whereas previous findings show a negative effect of higher education on public transport use). In such a way one can utilize latent class analysis to identify such subgroups, which are otherwise difficult to be found. In this case, a subgroup of highly educated people behaved differently than other members of their group.

Detecting different classes has important implications for designing future successful intervention studies. The attributes number of children or income turn out to be important to differentiate between people who allocate high importance to money and time considerations, and others who allocate a lower importance to them. A future intervention study could adapt itself to such a diagnosis. Different interventions could be used for individuals belonging to different classes in the design of future experiments.

Three types of information were not postulated by theory, and were deduced from data analysis in this study: change over time, association between slope and intercept and the number of classes. Such results should be included in theory building in future research, so that one would be able to test them rather than conduct inductive model estimation.

One potential drawback of the mixture growth approach discussed by Li et al. (2001) is that there is no guarantee for model convergence. Fortunately, STREAMS overcomes this problem by employing as starting values results of previous models. However, even when convergence is achieved, it is possible that different solutions may be found using different starting values. Another potential drawback is that the model assumes the same measurement and structural model for all the latent classes, although this may not be the case in practice. However, growth mixture modelling is an important development in the study of change, and contributes to a better understanding of processes over time. It takes observed and unobserved heterogeneity of samples into account instead of ignoring it.

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Appendix A

Model Building Language Statements

```
****************************************************************************
* TI growth model total population with missing 1009
* MO PR=eldad NAME=MixGrowt4_t
* MO Create instructions for: Mplus
* MO Means included in model     One-group model
* MO Mplus 3.0
* STA NAME=grow4t
* STA NAME=grow5t
* STA NAME=grow6t
* STA NAME=mix4
* STA NAME=MixGrowt1
* STA NAME=MixGrowt3
* OP ANAL TYPE=MIXTURE;
* OP ANAL ESTIMATOR=MLR;
* OP ANAL ALGORITHM=EM;
* OP ANAL TYPE=MEANSTRUCTURE MISSING;
* OP OUTP TECH1;
* OP MPL GRO I S | BE1MB@0 BE2MB@1 BE3MB@2;
* OP DEFI ALT1=ALT1/10;
* POP C1 C2 C3 C4
* DAT FOLDER=RAW DATLAB=MISSING
* MVR B104A B104B B104C B112B B112C B112D B112F GEN1 ALT1 CHL1 AC1
EDU1
* INC1 INV1 BE1MB BE2MB BE3MB
* LVR I S C#1 C#2 C#3
* REL C1 C2 C3 C4 INV1 -> S
* REL C1 C2 C3 C4 GEN1 ALT1 CHL1 EDU1 AC1 INC1 -> I S
* REL C#1 C#2 C#3 -> I S
* REL GEN1 CHL1 INC1 -> C#1 C#2 C#3
* COV C1 C2 C3 C4 I& S&
* MEA C1 C2 C3 C4 B104A B104B B104C B112B B112C B112D B112F
* MEA C1 C2 C3 C4 I S
****************************************************************************
```

Explanation: The modelling process is done in three steps. The first step is the growth model. In the second step we estimate a latent class model. In the third step we joined the two models into a growth mixture model. The effects of the socio-demographic variables on the latent class variables and on the intercept and slope growth factors differ across different classes. For a graphical representation see figure 1.

Table 1: Description of Variables in the Study (N = 774).

Variable	Description	Mean (Std. deviation in Brackets)
Behavior: BEH1MB, BEH2MB, BEH3MB	1=public transport, bicycle or walking; 0=car use	
	BEH1MB-1st wave	0.51 (0.50)
	BEH2MB-2nd wave	0.50 (0.50)
	BEH3MB- 3rd wave	0.49 (0.50)
Intervention Program-INV1	1=belongs to experimental group (receives information as an intervention); 0=control group, no information received	0.75 (0.43)
	For variables B104A, B104B and B104C the scale is 1=totally disagree; 2= disagree; 3= neither agree nor disagree; 4= agree; 5= totally agree	
B104A	Since the increase of fuel prices I am angry on the costs of the daily use of the car in Frankfurt	3.08 (1.46)
B104B	Since the increase of fuel prices using the car in Frankfurt daily involves higher costs than planned	2.89 (1.45)
B104C	Since the increase of fuel prices driving the car daily in Frankfurt is too expensive	3.07 (1.44)
	For variables B112B, B112C, B112D and B112F the scale is 1=very unlikely; 2=unlikely; 3= neither unlikely nor unlikely; 4= likely; 5= very likely	
B112B	If I use public transport rather than the car in the next weeks in Frankfurt, it will involve a long waiting time for the next connection	3.74 (1.34)
B112C	If I use public transport rather than the car in the next weeks in Frankfurt, I will save the time costs and anger caused by looking for a parking place	4.00 (1.28)
B112D	If I use public transport rather than the car in the next weeks in Frankfurt, I will not be in a traffic jam	3.85 (1.23)
B112F	If I use public transport rather than the car in the next weeks in Frankfurt, I will be in the destination more quickly than with the car	3.86 (1.41)
GEN1	Gender 1=males; 2=females	1.52 (0.50)
CHL1	Number of children in the household	0.39 (0.77)
EDU1	Education level: 1=no formal education; 2=elementary school; 3=high school; 4= high school with matriculation; 5=higher education	3.63 (1.15)
INC1	Net income of the household: 1= less than 1000 Euros; 2= 1000 to 1999 Euros till 7= 6000 Euros or more	2.99 (1.38)
AC1	Availability of a car in the household 1= always; 2= sometimes; 3=seldom; 4=never.	1.48 (0.90)
ALT1	Age	44.22 (15.70)

Table 2. Information criteria indices and entropy values for latent class models.

Models	No. of free parameters	AIC	BIC	Sample-size adjusted BIC	Entropy
Model 1 (with 1 class)	14	31479.4	31552.1	31507.7	-
Model 2 (with 2 classes)	22	29922.7	30036.9	29967.1	.832
Model 3 (with 3 classes)	30	29276.3	29432.1	29336.8	.838
Model 4 (with 4 classes)	38	28808.2	29005.5	28884.8	.863
Model 5 (with 5 classes)	46	28410.5	28649.4	28503.3	.845

Table 3. Estimated mean of the intercepts and slopes in the latent groups

	Class 1	Class 2	Class 3	Class 4
Intercept	-.72	.33	.57	.99
Slope	-.32	-1.23	1.32	.08

None of these estimates is statistically sig. at .05.

Table 4. Latent group differences in the effects of background variables on intercept and slope (standardized estimates)

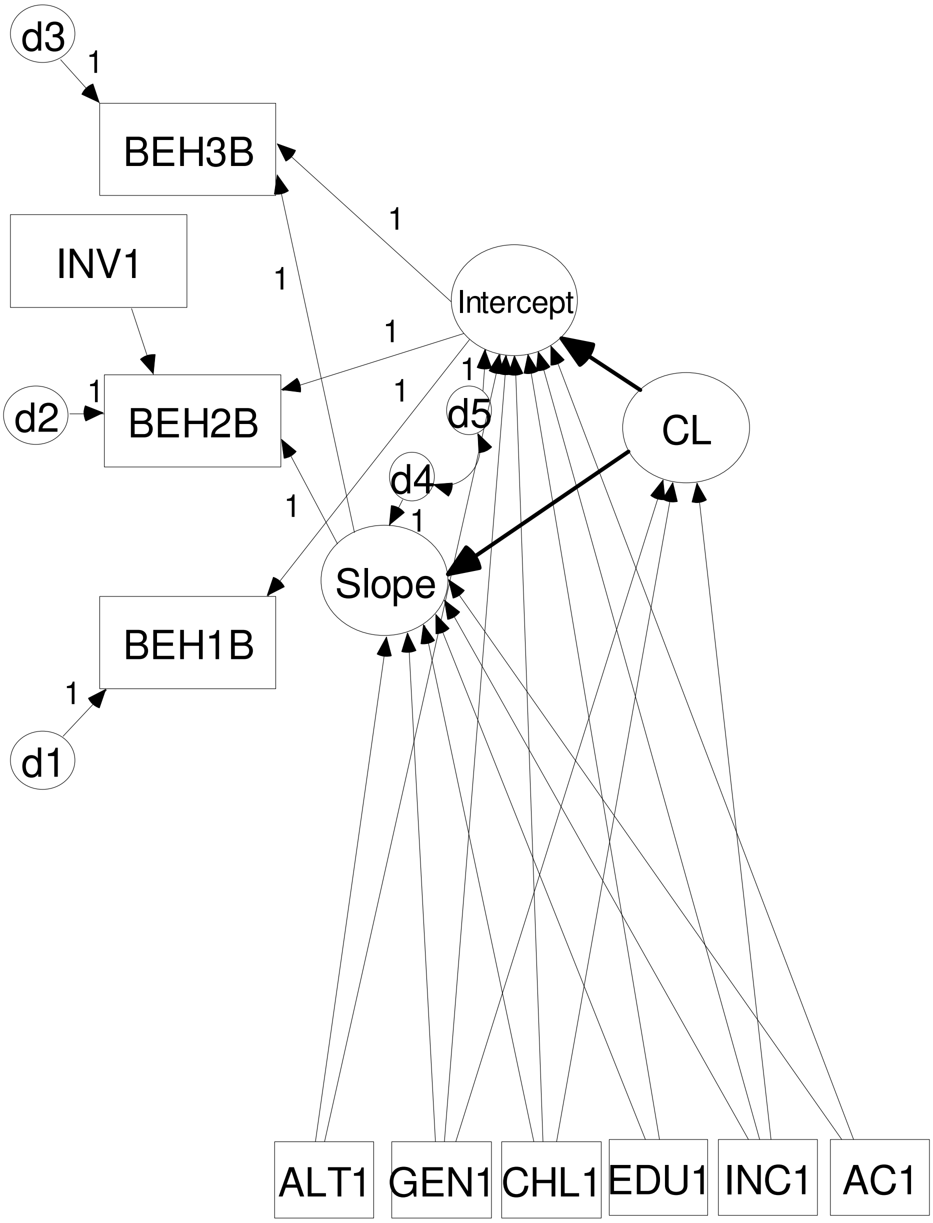
	Class 1		Class 2		Class 3		Class 4	
	Intercept	Slope	Intercept	Slope	Intercept	Slope	Intercept	Slope
GEN1	0.195	-0.319	0.162*	-0.080	0.150**	-0.155	0.132	-0.056
ALT1	-0.065	-0.118	0.020	0.143	0.044	0.260	0.185**	-0.220
CHL1	-0.061	-0.081	-0.084	0.009	-0.205**	0.264*	-0.199**	0.119
AC1	0.644**	0.240*	0.525**	-0.318	0.554**	-0.134	0.498**	0.104
EDU1	-0.236*	0.330	-0.249**	0.005	0.065	-0.128	0.275**	-0.094
INC1	0.372**	-0.404	0.019	0.387**	0.020	0.048	-0.213**	0.463

** p<0.05; *p<0.1

Table 5. Differences between groups in the regression coefficients of background variables (unstandardized coefficients)

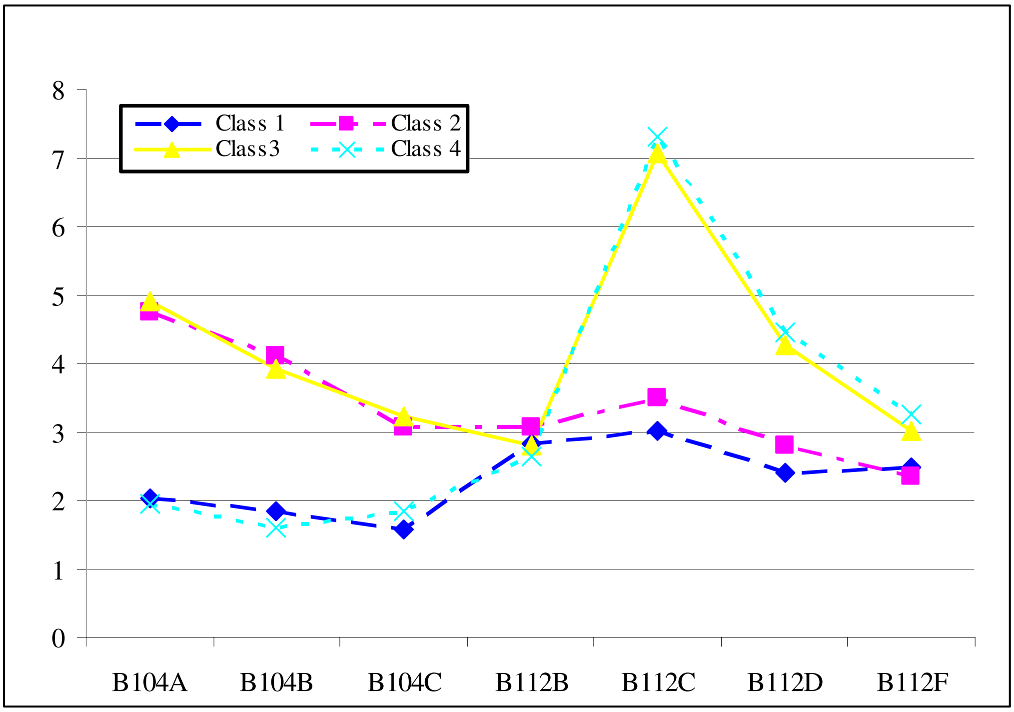
	Estimates	SE	T-values
Class 1 ON			
GEN1	-0.044	0.288	-0.154
CHL1	0.114	0.167	0.684
INC1	0.186	0.096	1.932
Class 2 ON			
GEN1	0.071	0.202	0.351
CHL1	0.207	0.130	1.594
INC1	0.068	0.068	0.989
Class 3 ON			
GEN1	-0.035	0.163	-0.215
CHL1	0.099	0.117	0.850
INC1	-0.179	0.061	-2.924
Class 4 ON			
GEN1	0	-	-
CHL1	0	-	-
INC1	0	-	-

Figure 1: A Growth Mixture Model to Explain Travel-Mode Choice



Legend:
ALT1-age; GEN1-gender; CHL!-number of children; EDU1-level of education; INC1-income; AC1-availability of a car; BEH1B, BEH2B, BEH3B- behaviour at time points 1 to 3; INV1-intervention; CL-class; d1-d5- stochastic errors

Figure 2. Plot of the latent classes (based on estimated means) (on the y-axis are the mean values of each variable on the x-axis in each class)



[1] Availability of a car was found out in several studies (for example Bamberg & Schmidt, 2001) to have a strong influence on travel mode choice. However, it did not appear in the German micro-census data set, which was applied in Davidov et al. (2003) and therefore its effect could not be tested.

[2] Such a response rate is normal for this design. It did not affect the internal validity of the study, since the respondents were randomly divided into an experimental and a control group. The two groups did not differ in respect to important socio-demographic characteristics. The randomization took place after the first wave.

[3] There was no difference in the change pattern between the dichotomous variable behavior on the second reported day and a behavioral variable averaging travel mode choices over that day. The two variables had a correlation of about 0.8 in each wave.

[4] Like AIC, BCC and CAIC, the BIC is a statistic intended for model comparison, and stands for Bayes information criterion (for details see Schwarz, 1978; Raftery, 1993; Dayton 2003). However, in comparison to the AIC, BCC and CAIC, the BIC assigns a greater penalty to model complexity, and so has a greater tendency to pick parsimonious models.